Bank Liquidity Regulation and the Growth of Private Credit

Sebastian Doerr

BIS & CEPR

Gaston Gelos

BIS & CEPR

Vesa Pursiainen

University of St.Gallen & Swiss Finance Institute

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Abstract

We study the role of bank liquidity regulation in the growth of private credit. Following the introduction of the liquidity coverage ratio (LCR), private credit increases significantly more in U.S. counties where banks subject to the LCR or where LCR-banks with a greater initial liquidity shortfall had a larger footprint. Our estimated effect of the LCR on private credit growth is comparable in economic magnitude to that of the capital shock from stress tests. The relationship between LCR footprint and private credit is stronger in industries that are more reliant on credit.

JEL Codes: G21, G23, G28.

Keywords: private credit, liquidity regulation, liquidity coverage ratio, nonbank lending

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Sebastian Doerr (sebastian.doerr@bis.org) and Gaston Gelos (gaston.gelos@bis.org) are at the Bank for International Settlements and CEPR. Vesa Pursiainen (vesa.pursiainen@unisg.ch) is at the University of St.Gallen and Swiss Finance Institute. We would like to thank Mathias Drehmann, Jon Frost, Denis Gorea, Mikael Paaso, Mingzhu Tai, and seminar participants at the BIS for helpful comments. Vesa Pursiainen gratefully acknowledges financial support by the Swiss National Science Foundation, grant no. 10001196. The views expressed here are those of the authors only, and not necessarily those of the Bank for International Settlements.

1 Introduction

Following the financial crisis of 2008-2009, the Basel Committee introduced global liquidity standards to mitigate the liquidity risks arising from funding illiquid assets with short-term liabilities. These standards resulted in the introduction of the Liquidity Coverage Ratio (LCR) requirement for large banks – implemented in the United States in 2013. Under this regulation, banks with more than $50 billion in total assets (LCR banks) are required to hold high-quality liquid assets (HQLA) to cover at least the expected net cash outflows during a 30-day stress period. This led to an increase in the share of HQLA among affected banks, but also to crowding out of bank lending and a migration of liquidity risk to non-LCR banks (Roberts et al. (2023); Sundaresan and Xiao (2024)).

The onset of liquidity regulation has coincided with a dramatic increase in private credit, originated directly by nonbanks and held on the balance sheets of private credit funds and business development companies (BDCs).[1] While a number of studies suggest that bank regulation is an important factor shifting lending from banks to nonbanks, essentially all of these papers focus on bank capital requirements.[2] While liquidity regulation is the other major component of bank regulation, there is no existing evidence of its effect on the growth of nonbank lending.

In this paper, we study to what extent liquidity requirements contributed to the growth of private credit. Base on loan-level data from Pitchbook, we construct a comprehensive sample of private credit in the U.S. We aggregate the data to quarterly outstanding direct loan volumes by county, based on the borrower firm location. We then construct two county-level measures of the footprint of LCR banks to capture differences in exposure to the LCR regulation, as of 2012, i.e. before the regulation was implemented. The first measure, *LCR footprint*, is the deposit share of LCR banks in the county. The second, *LCR gap footprint*, is the deposit-weighted estimated LCR gap, calculated as the bank-level shortfall relative to the regulatory LCR requirement, as in Sundaresan and Xiao (2024).

We begin our analysis by plotting quarterly county-level private credit volumes around the introduction of the LCR, divided into high and low LCR footprint

[1] See, e.g., Avalos et al. (2025), Ivashina (2025).

[2] See, e.g., Irani et al. (2021), Begenau and Landvoigt (2022), Chernenko et al. (2022), Davydiuk et al. (2024), Lee et al. (2024), Bednarek et al. (2025).

counties. Prior to the LCR, both sets of counties exhibit similar trends. Following the LCR introduction in 2013, private credit volumes increase substantially more in counties with a larger footprint of banks subject to the LCR.

We then perform regression analyses to examine the effects of the LCR on the evolution of private credit at the county level. Regressions control for county and time fixed effects, capturing any non-time-varying differences between counties, as well as any factors contributing to the general growth in private credit over time. We find that private credit increases significantly more in counties that are more affected by the LCR. This is true for both the binary measure of LCR banks' footprint, as well as the LCR gap measure. The result is also robust to including state×year fixed effects. Finally, and consistent with results driven by changes in credit supply, effects are stronger in industries that rely more on credit as a source of funding.

The economic magnitude of the estimated effect is large. A one-standard-deviation higher ex-ante footprint of LCR banks in the county results in nearly 50% higher private credit volumes following the introduction of the LCR. Breaking down the regression analysis into quarterly coefficients for the LCR fooprint shows that there are no differences in the pre-trends before the LCR introduction, and that the timing of the increase in private credit volumes coincides closely with the regulation.

Prior research has shown that the LCR regulation increases banks' HQLA share.[3] It also crowds out some lending that banks would have done in the absence of the regulation (Reinhardt et al., 2023; Roberts et al., 2023; Sundaresan and Xiao, 2024). Our results suggest that this decrease in bank lending is at least partly offset by an increase in private credit – possibly shifting some of the liquidity risk from banks to private credit funds and BDCs.

A number of papers find that bank capital regulation shifts lending away from banks into nonbanks.[4] To compare the role of liquidity regulation against that of capital regulation, we use the CCAR stress test in 2012 as a shock to bank capital (as in e.g. Cortés et al. (2020)). We calculate similar county-level bank footprint

[3]See Doerr and Drehmann (2025) for a survey of the academic literature. See BCBS (2019) for a Basel Committee survey.

[4]See, e.g., Irani et al. (2021), Begenau and Landvoigt (2022), Chernenko et al. (2022), Davydiuk et al. (2024), Lee et al. (2024), Bednarek et al. (2025).

measures as for the LCR, using i) a dummy indicating whether the bank underwent the stress test and ii) the Tier 1 capital gap (or shortfall) revealed by the stress test. We normalize both the LCR and stress test footprint measures by scaling them with their standard deviation. This allows us to directly compare the estimated effect of capital regulation against that of liquidity regulation.

We find that both the LCR and the stress-test-induced capital shock are followed by a significant increase in private credit volumes in areas where affected banks have a larger initial footprint. Furthermore, the economic magnitude of the estimated effects of the LCR and the stress test on the increase in private credit is comparable. Using the footprint measures based on binary bank indicators, the effect of the LCR is larger and dominates when both measures are included in the same regression. Using the continuous bank measures for LCR and capital shortfall, the Tier 1 capital gap footprint has a slightly larger coefficient estimate than the LCR gap footprint, both individually and when included in the same regression. Taken together, these results suggest that liquidity regulation is an important but often overlooked component of bank regulation when discussing the regulatory-induced shift of lending from banks to nonbanks.

Our findings a robust to various extensions. We confirm that our main findings are robust to alternative measures of private credit growth; the inclusion of industry× year fixed effects; and when we exclude loans for leveraged buyouts (LBOs) from the sample. Moreover, results are robust to controlling for average bank size, population density, or deposit market competition, in each county. Finally, we examine leveraged loans. Leveraged loans represent a product segment that partly overlaps the likely target segments of private credit providers (Ivashina (2025)). They are originated by banks but generally not held on the balance sheets of banks (Blickle et al. (2022)). Hence, they should not be substantially affected by the LCR regulation. We find no significant change in leveraged loan volumes conditional on counties' LCR exposure. This suggests that our results on private credit are unlikely to be driven by changes in loan demand.

Our findings are an important addition to earlier evidence that liquidity regulation has crowded out some lending from affected banks. (Sundaresan and Xiao (2024), Banerjee and Mio (2018)). Other studies suggest other margins of substitution, including loan pricing (Bonner and Eijffinger (2016)), cross-border lending

(Reinhardt et al. (2023)), intra-financial loans (Banerjee and Mio (2018), and asset complexity (Raz et al. (2022)), wholesale funding costs Aldasoro et al. (2026), as well as a shift towards less-regulated smaller banks in the U.S. (Sundaresan and Xiao, 2024). We show that the LCR has also shifted lending from banks to nonbank lenders, in particular private credit funds. This is likely a positive development from the viewpoint of systemic liquidity risk. Private credit funds are less exposed to liquidity risk, substantially less levered than banks (Block et al. (2024),Chernenko et al. (2025)), and hence arguably better-suited to fund illiquid assets. These findings add to the so far limited but growing literature on bank liquidity regulation (Diamond and Kashyap (2016), Doerr and Drehmann (2025)).

We also contribute to the understanding of the drivers of private credit. The market that has grown rapidly in the past decades and become a major source of funding for various types of firms. Low interest rates and reach for yield as well as bank capital regulation are often-cited macro drivers (e.g., Avalos et al. (2025), Ivashina (2025)). On bank capital regulation, both theoretical and empirical work suggests that higher bank capital requirements can decrease bank lending (e.g. Cortés et al. (2020), Begley and Srinivasan (2022), Bord et al. (2021)) and shift lending to nonbank lenders (Begenau and Landvoigt (2022), Irani et al. (2021), Chernenko et al. (2022), Loumioti (2022), Davydiuk et al. (2024), Lee et al. (2024), Bednarek et al. (2025)). The implications of this may not be always positive. For example, Aldasoro et al. (2025b) find that nonbank lenders curtail their syndicated lending by significantly more than banks during financial crises in borrower countries. Buchak et al. (2018) shows that bank regulation has also contributed to the rise of fintech lenders. Our study highlights the important role of liquidity regulation in explaining these developments.

2 Institutional background and data

This section first provides institutional background on the LCR and private credit. It then discusses the data and the construction of the main variables used in our analysis. Finally, it reports summary statistics for our sample of banks and counties.

2.1 Institutional background on the LCR

During the great financial crisis (GFC), wholesale funding markets froze and even well-capitalized banks suffered from liquidity shortages. In response, the 2010 *Basel III: International Framework for Liquidity Risk Measurement, Standards and Monitoring* placed liquidity risk on an equal footing with solvency risk and introduced the Liquidity Coverage Ratio (LCR). The LCR aims to ensure that banks can survive a 30-day stress episode.[5]

The LCR requires the ratio of an institution's stock of HQLA to its projected net cash outflows over a 30-day period of market and idiosyncratic stress to exceed 100%. In other words, it requires banks' liquid assets to exceed their near-term runnable liabilities:

$$\text{LCR} = \frac{\text{Stock of HQLA}}{\text{Total net cash outflows over 30 days}} \geq 100\%.$$

To determine the quantity of HQLA required, banks must apply outflow and inflow rates prescribed by regulation to their different sources of funding, obligations, and assets. For the numerator, only assets that demonstrably retain value and marketability in periods of strain qualify for the buffer. There are two categories. *Level 1 assets* carry no haircut and may make up 100% of the stock of HQLA. These include cash, central bank reserves, and highly rated sovereign or central bank securities. *Level 2 assets* are subdivided into Level 2A assets (for example, certain high-grade public-sector or covered bonds) and, at national discretion, Level 2B assets (for example, lower-rated corporate debt or equities in major indices). Level 2 holdings are subject to mandatory haircuts of at least 15% (Level 2A) or 25–50% (Level 2B) and together may not exceed 40% of the total stock, with Level 2B capped at 15%.

For the denominator, projected net outflows are calculated under a 30-day stress scenario. Net outflows are the difference between total expected cash outflows and total expected cash inflows. Total expected cash outflows are calculated by multiplying the outstanding balances of various categories or types of liabilities and off-balance sheet commitments by a run-off rate. Total expected cash inflows are

[5]In addition, the Net Stable Funding Ratio (NSFR) was introduced. We concentrate on the LCR because it focuses on short-term resilience to immediate liquidity stress. The NSFR targets longer-term structural funding stability by aligning asset maturities with durable funding sources.

calculated by multiplying the outstanding balances of various categories of contractual receivables by the rates at which they are expected to flow in under the scenario up to an aggregate cap of 75% of total expected cash outflows.

The Basel Committee issued a revised LCR rule in January 2013. In the U.S., the LCR was first proposed in October 2013 and finalized in September 2014. The final compliance deadline was December 2017. Banks with assets above $50 billion are subject to the LCR, but to a different extent. The required LCR is 100% for banks with assets above $250 billion. It is 70% for banks with assets between $50 billion and $250 billion.

As discussed in the survey by Doerr and Drehmann (2025), banks mostly responded to the LCR by increasing their HQLA at the expense of their lending. To a much lesser extent they replaced short-term wholesale funding with more stable retail or longer-maturity liabilities. The finding that banks mostly adjusted their stock of HQLA in response to the LCR is also confirmed in a survey-based analysis by the BCBS (2019). As discussed in the literature review, a large body of work finds that U.S. banks (as well as banks elsewhere) subject to the LCR saw a significant decline in their lending activity (Bonner and Eijffinger, 2016; Curfman and Kandrac, 2022; Reinhardt et al., 2023; Roberts et al., 2023; Sundaresan and Xiao, 2024).[6]

2.2 Institutional background on private credit

Private credit has seen spectacular growth in many jurisdictions. In the U.S., total outstanding loan volumes have increased from around $90 billion in 2010 to over $1 trillion today (Avalos et al., 2025). Private credit generally refers to nonbank credit extended by specialized investment vehicles ("funds") to small and mid-sized non-financial firms (Block et al., 2024; Ivashina, 2025). In addition to the type of borrowers served, the private credit market differs from syndicated or leveraged loans in two important respects. First, private credit deals are usually directly negotiated between a borrower and a lender, rather than arranged by investment banks and comprising a large group of lenders. Second, private lenders hold loans on

[6] In the Internet Appendix we replicate the result in Sundaresan and Xiao (2024) showing that banks with a larger LCR gap cut their lending by relatively more after the introduction of the LCR (see Table IA.1).

their balance sheet until maturity, rather than selling them in an active secondary market.

The universe of private credit funds comprises various players that differ in the structure of their liabilities and/or assets. Most funds operate as closed-end structures that lock in capital for their entire life cycle, typically ranging from five to eight years. They do not trade publicly and are not available to retail investors, which makes them illiquid and subject to lighter regulation. However, some fund structures that offer investors more frequent redemption opportunities have grown in popularity. An important example are business development companies (BDCs), many of which list their shares on stock exchanges and are accessible to retail investors (Davydiuk et al., 2024). In general, retail investors have become more important in recent years (Aldasoro et al., 2025a).

Individual funds usually specialize in certain strategies. 'Direct lending', which typically refers to funds extending covenant-heavy floating-rate loans to small or mid-sized firms, is most commonly associated with private credit. It is often considered as the typical example of so-called unsecured cash-flow lending, which relies on cash generation from firms' regular operations instead of collateral. Other strategies include mezzanine, which involves junior or subordinated lending to larger firms (often with equity participation rights), asset-based finance, which requires hard assets as collateral, or funds that specialize in distressed assets such as non-performing loans. While initially private credit mostly funded LBOs, the share of LBO direct loans has substantially declined over the past 15 years (Aldasoro and Doerr, 2025).

2.3 Data and variable construction

The LCR and banks' geographic footprint. We follow Hong et al. (2014) and Sundaresan and Xiao (2024) to compute the LCR for each bank holding company (BHC) from U.S. call reports data.[7] We then define two variables. First, we define the dummy $1(LCR)_b$ that equals one if bank b is subject to the LCR (i.e., has total assets exceeding \$50 billion), and zero for banks not subject to the LCR. Second, we compute the $LCR\ gap_b$ for bank b as $Required\ LCR_b - Pre\text{-}regulation\ LCR_b$. The required LCR is 100% for banks with assets exceeding \$250 billion and 70% for

[7]For details, see Hong et al. (2014) and Sundaresan and Xiao (2024).

banks with assets exceeding $50 billion but below $250 billion. This variable is only defined for bank subject to the LCR. As shown in Sundaresan and Xiao (2024), banks subject to the LCR as well as banks with a larger LCR gap saw a relatively stronger contraction in lending.

To compute banks' regional footprint, we combine these bank-level measures with branch-level data on bank deposits. Information on local deposits is obtained from the FDIC's Summary of Deposits Statistics (SOD). We compute the ex-ante (as of 2012, i.e., pre to the LCR phase-in) geographic footprint at the county level in two ways:

$$\text{LCR footprint}_c = \sum_b \frac{deposits_{b,c}}{deposits_c} \times 1(LCR)_b \tag{1}$$

and

$$\text{LCR gap footprint}_c = \sum_b \frac{deposits_{b,c}}{deposits_c} \times LCR\ gap_b. \tag{2}$$

Intuitively, the variable *LCR footprint* measures the share of local deposits held in branches of banks subject to the LCR prior to the introduction of the LCR. The variable *LCR gap footprint* focuses only on deposits of LCR banks and takes on a higher value if banks with a larger ex-ante LCR gap (i.e., a larger liquidity shortfall) had a larger local footprint. The first variable thus captures the market share of LCR banks, while the second variable captures the intensity of the LCR's impact on banks subject to the LCR.

In addition, we define the following variables. First, the dummy *stress-tested* that equals a value of one for banks subject to CCAR stress tests in the post-crisis period and zero otherwise. Second, the variable *Tier-1 gap* captures a potential decline in banks' capital under stress and equals the difference between the BHC's current capital ratio and the lowest implied capital ratio expected under the severely adverse stress-test scenario. This measure of a capital shortfall is taken from Cortés et al. (2020). For both measures, we again compute the regional footprint via local deposits.

Private credit data. We use data on private credit deals involving U.S.-based borrowers provided by Pitchbook Data, Inc (Pitchbook). For each deal, Pitchbook provides the originating private credit fund(s), the borrowing firm, the outstanding amount, the interest rate spread (over standard reference rates such as LIBOR or SOFR), both start and end date of the loan (maturity), as well as certain borrower information, such as its identifier, location, and industry. In addition, we know the loan purpose (e.g. leveraged buyout (LBO)) and whether the loan is secured or not.

We construct each lender's outstanding loan volume as a stock variable to proxy the loan's entry on lenders' loan books in each quarter. Each outstanding loan remains active until it matures (Jiménez, Ongena, Peydró, and Saurina, 2014; Morais, Peydró, and Ruiz, 2019; Doerr and Schaz, 2021).[8] Note that this approach implicitly assumes that loans are not sold on secondary markets, which a reasonable assumption for private credit: By its very nature (and in stark contrast to e.g. syndicated loans), the loan originator generally keeps the loan on its balance sheet until maturity. For example, a private loan issued in 2005 with a maturity of five years remains active until 2010.

In our main regressions, we aggregate all outstanding loan volumes to the county-quarter level to obtain total outstanding direct loan volumes to all firms in county c in quarter t. The total loan volume in a given quarter hence corresponds to the sum of the value of all outstanding (new as well as continuing loans) from all lenders to firms in a given county.

Other county data. We collect yearly county-level data on the unemployment rate, total population, poverty rate, house prices, income per capita, and area from Geo Fred. We compute county density as the ratio of total county population over county area.

2.4 Sample and summary statistics

Our sample period is 2010Q1–2019Q4 and observations are at the county-quarter level. We are able to compute the LCR for 6,772 unique BHCs, out of which 36 are subject to the LCR. 568 counties had positive private credit volumes during our

[8]When information on maturity is missing, we assume the loan's maturity to be the same as the average maturity across loans to firms in the same industry, as in Aldasoro and Doerr (2025).

sample period.

Figure 1 provides ex-ante summary statistics on the bank-level LCR and LCR gap for LCR and non-LCR banks. Consistent with the values reported in Hong et al. (2014) and Sundaresan and Xiao (2024), banks not subject to the LCR have a higher ex-ante computed LCR (mean 258%, median 184%) than banks subject to the LCR (mean 75%, median 65%). The LCR gap, computed only for banks subject to the LCR, has a mean and median of 14% and 10%, respectively (right axis). Over 75% of observations have a value greater zero, implying that the vast majority of banks subject to the LCR had realized values below the required ratios.

Table 1 provides summary statistics for our main variables. Panel a) reports county-level characteristics for the pre-LCR period (i.e., prior to 2013Q1). The average (median) deposit share of banks subject to the LCR is 44% (46%), reflecting that LCR banks are the largest banks in the U.S. For the LCR gap footprint, the mean and median values are both 6%. Table 2 shows that the correlation between the *LCR footprint* or the *LCR gap footprint* (as defined in Equations (1) and (2)) and county characteristics is mostly insignificant in the pre-LCR period. Panel b) reports information on private credit at the county-quarter level. In the mean (median) county-quarter cell, outstanding loan volumes equaled \$485 (\$63) million. Around one-third of loans are secured and around one-fifth for LBOs and buyouts. The maturity and spread of the average loan are 63 months and 7.38 percentage points (pps).

3 Empirical strategy and results

This section first discusses our empirical strategy and identifying assumptions. It then presents our main results.

3.1 Empirical strategy

Consistent with the literature, we categorize the quarters between 2010Q1 and 2012Q4 as the pre-LCR period and the quarters between 2013Q1 and 2019Q4 as the post-LCR period. Consistent with Roberts (2015), Bosshardt et al. (2024), and

Sundaresan and Xiao (2024), the LCR start date (2013Q1) is chosen as the quarter when the BCBS issued the revised LCR rule.

We estimate variants of the following regression.

$$Private\ credit_{c,t} = \beta\ LCR\ footprint_{c,2012} \times Post_t + \alpha_c + \gamma_t + \epsilon_{c,t}, \tag{3}$$

where c and t denote the county and quarter, respectively. In our baseline specification, the dependent variable is the natural logarithm of one plus the amount of private credit outstanding in county c in quarter t. We perform extensive robustness checks with alternative dependent variables. The variable $LCR\ footprint_c$ is the footprint of LCR banks, either based on the LCR dummy or LCR gap measure, as defined in Equations (1) and (2). *Post* is a dummy taking the value of one after the introduction of the LCR in 2013. We include county (α) and time (γ) fixed effects, controlling for any non-time-varying differences between counties, as well as the general growth in private credit over time. We also include the following county-level controls, all as pre-2013 values interacted with the post dummy: the unemployment rate, the poverty rate, total population, income per capita growth, and house price growth. Standard errors are clustered at the county level.

Identification. Our difference-in-differences specification exploits cross-sectional variation in counties' ex-ante exposure to the LCR (along the extensive as well as intensive margin) and compares the evolution of private credit before and after the reform. Identification of the coefficient on the interaction term requires that, absent the LCR, counties with different levels of the LCR footprint (and LCR gap footprint) would have followed parallel trends in private credit. We provide evidence on this assumption below. In addition the LCR gap provides a plausibly exogenous and pre-determined measure: among banks mechanically subject to the LCR because of size thresholds, those with larger pre-reform shortfalls faced tighter constraints for reasons that are likely orthogonal to local private credit conditions.

To mitigate concerns that differential local shocks might confound the estimates, our specification includes a rich set of fixed effects and controls. County fixed effects absorb all time-invariant differences in private credit levels and in local financial structure, while time fixed effects capture aggregate shifts in private credit supply and demand. For example, the overall increase in private credit is in part driven by reach-for-yield in the low-rate environment (Avalos et al., 2025; Ivashina, 2025). We absorb this aggregate trend through time fixed effects, instead identifying *where* private credit deployed its resources. In addition, interacting pre-LCR county characteristics with the post indicator flexibly accounts for differential trends linked to local economic fundamentals. In some specifications, we will also include state×time fixed effects to account for unobservable state-level trends.

That said, the correlations between the *LCR footprint* or the *LCR gap footprint* and several observable county characteristics are mostly insignificant in the pre-LCR period (Table 2 in the Online Appendix . In particular, the table reports results from county-quarter level regressions of the footprint measures on county characteristics over the pre-treatment years. For the *LCR gap*, only the coefficients on the poverty rate and the *Total assets footprint* are significant at the 10% and 1% level, respectively. The positive and significant coefficient on *Total assets footprint* is to be expected, as LCR banks are by definition larger banks. For the *LCR gap footprint* this significant correlation disappears and only the coefficient on the poverty rate remains significant at the 10% level. The coefficients on all other county characteristics, including the unemployment rate, income per capita (in levels and growth rates), house price growth, or population density, are statistically insignificant. These findings are reassuring in that the LCR footprint measures do not reflect unobservable county characteristics that could be systematically correlated with the growth of private credit.

3.2 The LCR and the rise of private credit

We begin our analysis by plotting the county-level amount of private credit outstanding in Figure 2, dividing counties into those with a high and low LCR footprint. In particular, we split counties into those in the top and bottom quartile of the LCR footprint distribution. Before the introduction of the LCR, the evolution of private credit follows the same trend in each group. Following the introduction of the LCR in 2013, private credit grows substantially faster in counties with a high LCR footprint (blue solid line) compared to those with a low footprint (black dashed line).

To more formally test for this relationship, we perform a regression analysis of county-level private credit on the county's ex-ante exposure to LCR, as specified in Equation (3). The results are shown in Table 3. Across all specifications, private credit increases significantly more in counties that are more affected by the LCR. This is true for both the binary measure of LCR banks' footprint, as well as the LCR gap measure.

The coefficient on the *LCR footprint* is positive and highly statistically significant (Table 3, column (1). In terms of magnitude, a 10% larger footprint of LCR banks in a county leads to a 20% increase in private credit volumes. Column (2) reports comparable results for the *LCR gap footprint.* We include state×time fixed effects in columns (3) and (4). These fixed effects control for any observable and unobservable trends at the state level. Even when we compare the effect of the LCR on private credit volumes across counties in the same state, we find near-identical effects to those in columns (3) and (4).

More formal analysis confirms the notion of a structural break in the relationship between private credit and our LCR footprint measures. To confirm the absence of pre-trends already shown in Figure 2, we replace the *Post* dummy in Equation (3) with indicator dummies for each quarter and interact them with the county-level measures of LCR exposure. We plot the coefficient estimates and associated 90% confidence bands in Figure 3. Before the introduction of the LCR, the estimated coefficients are very close to zero both for the LCR footprint (panel a) and the LCR gap footprint (panel b), while after the introduction the coefficients become positive and statistically significant.[9]

Robustness. We perform a large number of robustness tests. As we discuss below, our results are robust to controlling for observable and unobservable trends within each industry. Further, Table 6 shows that are results remain similar when we control for local bank size by computing the local footprint based on total assets of banks with deposits in each county interacted with the post dummy; as well as when we control for local population density interacted with the post dummy. Controlling for these factors ensures that our results do not mechanically reflect the

[9]These results mirror findings for bank lending, which show that banks with larger vs smaller LCR gaps did not see differential loan growth prior to the introduction of the LCR (Roberts et al., 2023; Sundaresan and Xiao, 2024). This rules out that banks with larger liquidity shortfalls were more aggressive lenders ex-ante.

presence of larger banks or that LCR banks have a higher presence in more densely populated urban areas. Table 7 further shows that are results are insensitive to the definition of the outcome variable: we find similar results when we use the log of the amount, the IHS transformation, or growth rates.

External financial dependence Our detailed deal-level data allow us to perform analyses at the more granular county-industry-quarter level, which brings several advantages. Estimating variants of Equation (3) broken down into different 3-digit SIC industries allows us to enrich the specification with more granular fixed effects. First, we include county×industry fixed effects, which control for time-invariant differences across industries within counties. For example, they absorb any effects that could stem from differences in the local industry structure. Second, we include time-varying fixed effects at the industry level. These fixed effects absorb any time-varying factors that affect industries, such as changes in loan demand. While in principle some industries could experience an increase in the demand for direct loans, and these industries could be relatively more important in counties with a larger LCR footprint, our fixed effects would absorb such factors. And third, we can exploit variation across industries within the same county in terms of their dependence on external funding.

Regression results using the industry-county-quarter as the unit of observation are consistent with our main results (Table 4, columns (1) and (2)). A higher LCR footprint/LCR gap footprint is associated with higher private credit volumes following the LCR introduction, even when controlling for industry dynamics.[10]

A priori, firms in industries that are more dependent on external financial should be more affected by the retrenchment of banks from lending to middle-market firms. Private credit should thus grow faster in these industries. We test this hypothesis dividing industries in our sample based on their external finance dependence, or EFD (Rajan and Zingales (1998)). Consistent with this argument, columns (3)–(6) in Table 4 confirm that the effects of the LCR and LCR gap footprint on the growth of private credit are stronger in industries with an above-median external financial dependence ('high EFD' industries).

[10] Table IA.2 shows that results are very similar without controlling for industry×time fixed effects, suggesting that industry-specific factors play a minor role in explaining our results.

3.3 Liquidity versus capital regulation

Our results suggest that bank liquidity regulation plays an important role in the growth of private credit. This finding complements prior evidence that bank capital regulation shifts lending away from banks to nonbanks (e.g., Irani et al. (2021), Begenau and Landvoigt (2022), Chernenko et al. (2022), Davydiuk et al. (2024), Lee et al. (2024), or Bednarek et al. (2025)). Given the similarity of these findings, it is natural ask to what extent the effect of liquidity regulation is different from that of capital regulation, and what relative importance each has in driving the growth of private credit.

To compare the role of liquidity regulation and that of capital regulation, we use the CCAR stress test in 2012 as a shock to bank capital. Regulators introduced annual stress tests to monitor the investment portfolios of systemically relevant banks in the United States. Stress tests assume adverse economic scenarios, for example rising unemployment and falling house prices. For each scenario, an internal model predicts banks' hypothetical losses given their asset portfolios. These losses are then projected into minimum capital ratios that would be required for banks to withstand the downturn. If financial institutions fail a test they must adjust their equity and may not distribute capital over the following quarters.

Following Cortés et al. (2020) and Doerr (2021), we calculate similar county-level bank footprint measures as for the LCR, using i) a dummy indicating whether the bank underwent a stress test in 2012 and ii) its Tier-1 capital gap based on the stress test. We normalize both the LCR and stress test footprint measures by demeaning them and scaling them with their standard deviation. This allows us to directly compare the effect of capital regulation to that of liquidity regulation.

The results indicate that both capital and liquidity regulations matter (Table 5). We first focus on the footprints based on dummy variables in columns (1)–(3). Both the LCR- and the stress-test-induced shock are followed by a large and significant increase in private credit volumes. Furthermore, the economic magnitude of the effects of the LCR and the stress test on the increase in private credit is roughly comparable when included separately (0.546 vs 0.398 for a one standard deviation increase in the footprint in columns (1) vs (2)). Including both measures in the same specification in column (3) shows the effect of the LCR to be larger and more significant. Using the continuous bank measures for the LCR and capital shortfall, the Tier-1 capital gap has a slightly larger coefficient estimate than LCR gap (column (4) vs (5)). When included in the same regression, this pattern holds (column (6)).

Taken together, these results suggest that liquidity regulation is an important but often overlooked component of bank regulation when discussing regulation shift of lending from banks to nonbanks. In addition, once can see the robustness of our results to controlling for stress test results as a validation that exposure to the LCR does not generally capture exposure to banks with weaker fundamentals.

4 Additional analysis and robustness checks

In what follow, we report additional robustness tests, address potential concerns regarding demand effects, and exploit heterogeneous effects of the LCR across industries and loan types.

4.1 Controlling for bank size and population density

A potential concern is that LCR footprint and LCR gap footprint are correlated with bank size, since the regulation only affects large banks. If private credit demand is concentrated in areas with a greater presence of large banks, our results could be driven by factors other than liquidity regulation but which are simply correlated with it. Another concern is that LCR banks are more active in more urban areas, which may be targeted by private credit funds. [11] To mitigate this concern, we perform a robustness check analysis where we control for the bank size distribution and local population density. We construct a deposit-weighted total assets measure for each county and compute density as total population over county area.

It turns out that that controlling for bank size or population density does not change our coefficient estimates much for LCR footprint variables much, suggesting

[11] As discussed above, Table 2 shows that the correlation between the *LCR footprint* and local bank size is significant and positive, but that it is statistically and economically insignificant for the *LCR gap footprint*. The correlation of either measure with population density is insignificant.

that our findings are not driven by a correlation between bank size and private credit(Table 6) .

4.2 Alternative outcome variables

Across our analyses, we use the natural logarithm of one plus the outstanding private credit as our outcome variable. We add one to retain observations with zero private credit in the sample. To make sure that our findings are not substantially affected by the specification of the outcome variable, we perform a robustness check analysis using three alternative outcome variables: the inverse hyperbolic sine of the private credit amount, natural logarithm without adding one – resulting in what is effectively an intensive margin analysis – and the quarterly change in private credit volume.

The results are shown in Table 7. Across all outcome variables, the results remain similar to our baseline specification. Counties with higher LCR footprint or LCR gap footprint exhibit significantly larger volumes and growth rates of private credit following the LCR introduction.

4.3 Leveraged loans and LBOs

Leveraged loans represent a product segment that partly overlaps the likely target segments of private credit providers (Ivashina (2025)). They are originated by banks but generally not held on the balance sheets of banks (Blickle et al. (2022)). Hence, they should not be substantially affected by the LCR regulation. If the increase in private credit was driven by a change in loan demand (or other factors such as capital regulation), instead of a liquidity regulation-driven shift in bank loan supply, we might expect similar patterns in leveraged loan volumes – providing a useful placebo test.

To test this conjecture, we construct a county-level dataset of leveraged loans, similar to our private credit sample. We then perform a regression analysis of leveraged loan volumes around the LCR introduction. We also repeat our baseline regression analysis of private credit volumes, but controlling for leveraged loan volumes in the same county.

The results suggest that our results on private credit are unlikely to be driven by changes in loan demand (Table 8). In columns (1) and (2) we find no significant change in leveraged loan volumes conditional on counties' LCR exposure. In columns (3) and (4), we show that our main results are also robust to controlling for leveraged loan volumes in the county.

In our private credit data, we can further distinguish between loans financing LBOs and other loan purposes. Since LBO loans originated by banks are typically not held on bank balance sheets, they should be less affected by bank liquidity regulation. To test this, we divide the county-level private credit volumes into LBO and non-LBO loans and repeat our baseline regression analysis for each subsample.

The results are shown in columns (5) to (8) of Table 8. The LCR does not have a significant effect on private credit financing LBOs, while non-LBO private credit increases significantly following the LCR introduction. This is consistent with the cross-sectional differences in private credit growth being driven by banks' balance sheet constraints, because LBO loans are not substantially affected by them.

4.4 Asset redeployability

Finally, we move back to the county-industry-time level and divide the sample into high and low asset redeployability (AR) industries. An important conceptual distinction is between *regulatory* liquidity and *economic* (fire-sale) liquidity. The LCR treats virtually all corporate loans as non-HQLA, so from a purely regulatory standpoint they look similarly illiquid. Yet banks' ability to manage a binding liquidity constraint depends on the *economic liquidity* of their exposures: loans differ in how easily they can be unwound, refinanced, or recovered when funding becomes scarce. A natural proxy for this economic liquidity is the redeployability of the borrower's assets. When assets are highly redeployable, collateral can be sold to a broader set of buyers, recovery values tend to be higher, and the lender can more credibly treat the position as "monetizable" in stress. When assets are hard to redeploy, liquidation is slower and fire-sale discounts likely larger. This logic implies that a liquidity requirement can reshape credit supply even *within* the set of non-HQLA loans by increasing the shadow cost of holding exposures backed by low-redeployability assets.

To study the asset liquidity composition of the borrowers, we use the asset redeployability index of Kim and Kung (2017). They show that more redeployable assets exhibit higher recovery rates and are traded more actively in secondary markets – an important consideration when lending against such assets.[12]

We find that the relationship between the LCR footprint and private credit volumes is substantially stronger in low-asset-redeployability industries (columns (7)–(10) of Table 9). This suggests that the substitution of bank lending toward private credit is focused on the more illiquid assets both in terms of regulatory liquidity as well as other measures of underlying asset liquidity. From the point of view of the regulators, this could be interpreted as a positive development: liquidity risk is transferred away from banks, possibly even more so than implied by the changes in assets typically viewed as HQLA.

5 Conclusion

We study how bank liquidity regulation affects the allocation of credit between banks and nonbanks. Exploiting plausibly predetermined cross-county variation in the pre-reform footprint of LCR banks, we estimate a difference-in-differences design around the 2013 introduction of the liquidity coverage ratio in the United States. Counties with greater ex-ante exposure to LCR-constrained banks experience a significantly larger post-2013 expansion in private credit. The effect is economically large: a one-standard-deviation increase in the county LCR footprint is associated with roughly 50% higher private credit volumes after the reform. Results are similar when exposure is measured along the intensive margin using the deposit-weighted LCR gap, and they are robust to county and time fixed effects, state×time fixed effects, and interactions of pre-period county characteristics with the post indicator.

Several pieces of evidence sharpen interpretation toward a regulation-induced reallocation in credit supply. Event-time specifications show no differential pre-trends, with divergence emerging precisely at the onset of the LCR. Placebo regressions address concerns stemming from correlated changes in loan demand: leveraged loan

[12] On the redeployability and pricing of collateral, see, e.g., Lian and Ma (2021), Almeida and Campello (2007), Benmelech et al. (2005), Benmelech and Bergman (2009), Campello and Giambona (2013), Degryse et al. (2025).

volumes, which are originated by banks but typically not held on bank balance sheets, do not increase differentially with local LCR exposure. Moreover, the post-LCR increase in private credit is larger in industries with high external finance dependence, where bank retrenchment is most likely to bind. Moreover, the effect is concentrated in low-asset-redeployability industries, consistent with liquidity regulation increasing the shadow cost of holding economically illiquid exposures and thereby expanding the comparative advantage of private credit vehicles financed with patient long-term capital.

We also benchmark liquidity regulation against a prominent shock to bank capital. Using county-level exposure to the 2012 stress tests and associated Tier-1 capital shortfalls, we find that both liquidity and capital constraints predict subsequent private credit growth, with broadly comparable magnitudes when standardized. This comparison suggests that liquidity regulation is an empirically important, and often overlooked, contributor to the post-crisis migration of intermediation from banks to nonbanks.

These findings have direct implications for how liquidity requirements should be evaluated. If private credit partly offsets a contraction in bank lending, then the costs and benefits of liquidity regulation depend not only on bank balance sheets but also on the capacity and resilience of nonbank lenders. At the same time, substitution into private credit does not mechanically imply a reduction in systemic risk: it changes the location and form of liquidity and credit risk, potentially interacting with investor redemption features, bank–nonbank linkages, and covenant and maturity design. Quantifying these trade-offs is a fruitful avenue for future work.

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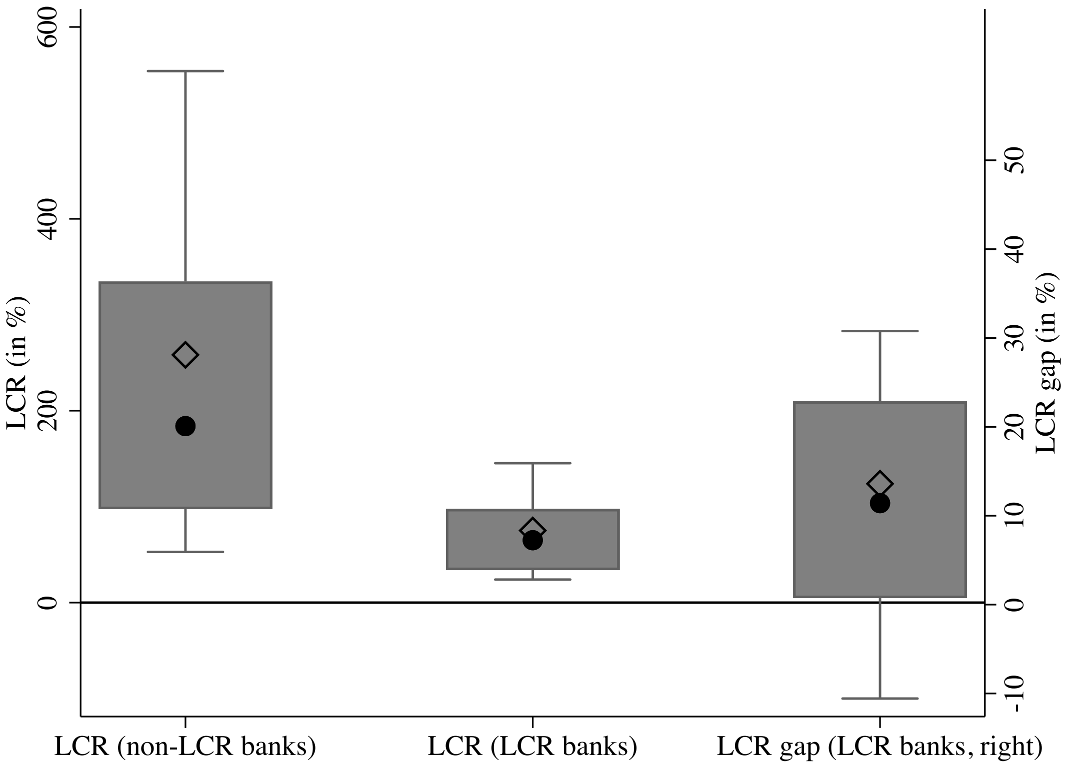
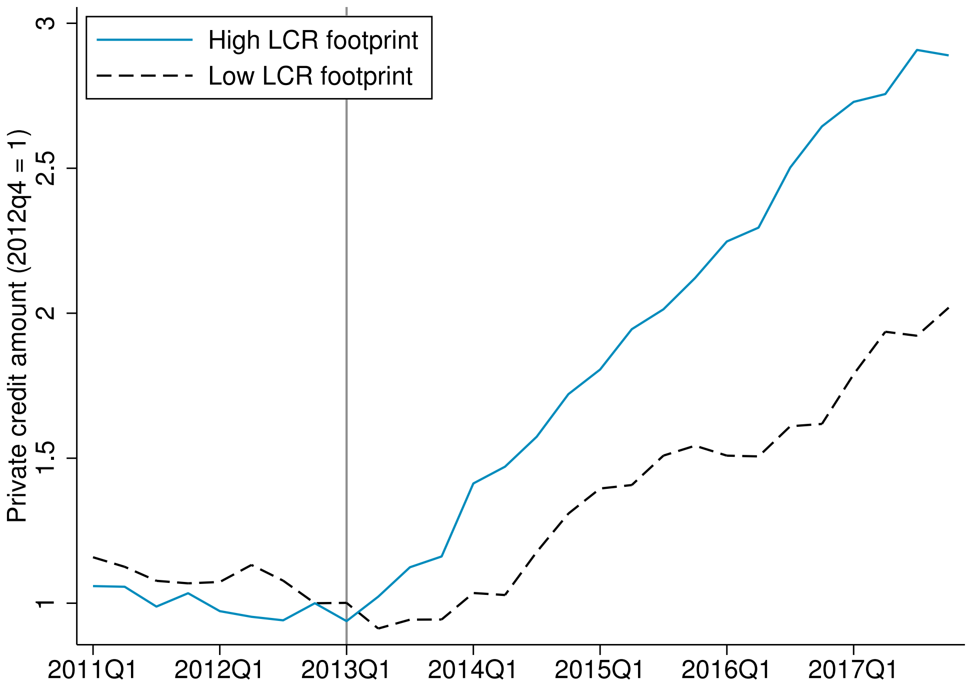
A Figures and tables

Figure 1: **LCR and LCR gap – distribution**



This figure shows the bank-level distribution of the estimated liquidity coverage ratio, as well as the LCR gap, as of 2012. The upper and lower end of the bars correspond to the 75th to 25th percentile of the distribution, the upper and lower tail of the whiskers to the 90th and 10th percentile. The black dot and diamond correspond to the mean and median values, respectively.

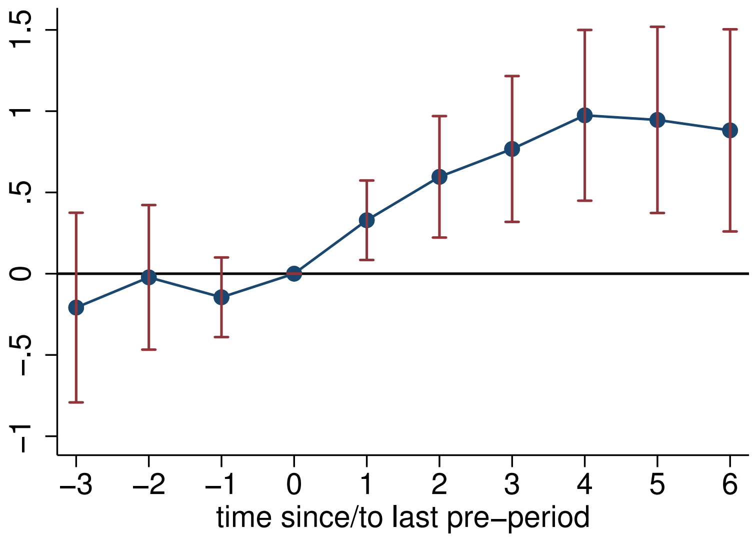
Figure 2: **LCR footprint and the growth of private credit**



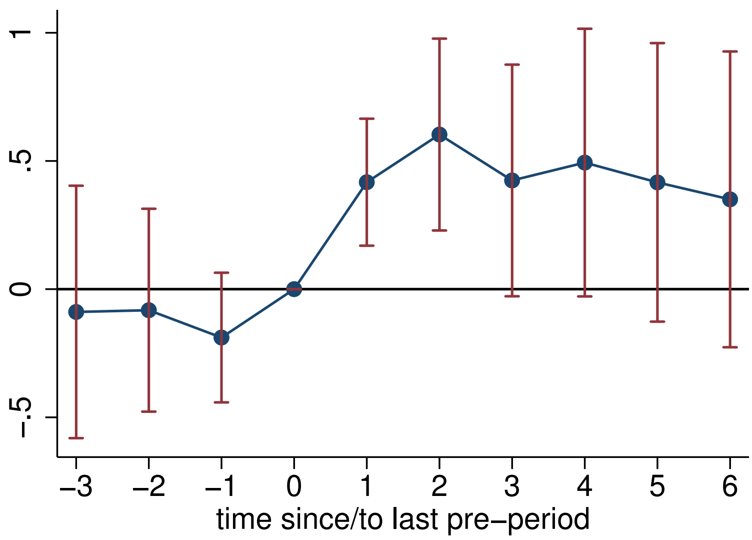
This figure shows the evolution of total private credit volumes at the county-level for counties with an LCR footprint in the top (high) vs bottom (low) quartile of the distribution.

Figure 3: **Private credit versus LCR footprint**

(a) LCR footprint



(b) LCR gap footprint



This figure shows quarterly coefficient estimates for *LCR footprint* and *LCR gap footprint* from regression equation (3), but where we interact the LCR measures with quarterly dummies. The dependent variable is the natural logarithm of one plus the outstanding private credit amount. A value of zero on the x-axis indicates Q4 2012, the quarter before the LCR was introduced in the U.S. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. The ranges indicate 90% confidence intervals.

Table 1: **Summary statistics**

Panel a): Ex-ante footprints and county characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
LCR footprint	2348	.44	.22	0	.86	.46
LCR gap footprint	2337	.06	.04	-.01	.16	.06
ST footprint	2442	.41	.23	0	.94	.41
Tier-1 gap footprint	2441	.02	.01	0	.04	.02
County unemp rate	2473	8.48	1.98	3.46	15.99	8.38
County poverty rate	2473	14	4.81	3.9	34.97	13.83
County income p.c. (in thd)	2449	44.17	12.59	22.85	126.02	41.13
County Δ income p.c.	2449	.04	.02	-.01	.19	.03
County population (in thd)	2473	545.52	827.9	3.91	9875.58	332.54
County Δ house prices	2418	-3.83	3.17	-16.01	8.13	-3.56

Panel b): Private credit

Variable	Obs	Mean	Std. Dev.	Min	Max	P50
Amount (in USD mn)	29178	485.64	1816.79	0	49986.17	62.52
log(amt)	29174	4.15	2.11	-3.51	10.82	4.14
log(1+amt)	29723	4.16	2.03	0	10.82	4.11
Share of secured loans	29178	.33	.38	0	1	.18
Share of buyout/LBO loans	29178	.18	.32	0	1	0
Maturity (in months)	29178	62.64	17.23	1	314	61
Rate spread	17894	7.38	2.8	.06	18	6.68

This table reports summary statistics for our main variables at the county level.

Table 2: **Balancedness**

VARIABLES	(1) LCR footprint	(2) LCR gap footprint
County unemployment rate	0.015	0.064
	(0.067)	(0.118)
County poverty rate	0.138*	0.209*
	(0.076)	(0.111)
County income p.c.	0.138	-0.075
	(0.095)	(0.117)
County Δ income p.c.	-0.065	0.055
	(0.062)	(0.081)
County population	0.006	-0.012
	(0.013)	(0.039)
County Δ house prices	-0.028	0.062
	(0.064)	(0.128)
County pop density	0.121	-0.078
	(0.110)	(0.206)
County area	-0.044	-0.044
	(0.033)	(0.069)
Total assets footprint	0.384***	0.125
	(0.058)	(0.085)
Observations	2,201	2,159
R-squared	0.358	0.088

This table shows results from a county-quarter level regression of the *LCR footprint* and *LCR gap footprint* (as defined in Equations (1) and (2)) on county characteristics over the pre-LCR period (2011–2012). Regressions cluster standard errors at the county level and weight observations by county population. All variables are de-meaned and standardized to a standard deviation of one.

Table 3: **County-level private credit versus LCR footprint**

VARIABLES	(1) log(1+amt)	(2) log(1+amt)	(3) log(1+amt)	(4) log(1+amt)
LCR footprint × post	2.012***		2.490***	
	(0.450)		(0.512)	
LCR gap footprint × post		7.523***		8.934***
		(2.347)		(3.053)
Observations	12,776	12,654	12,551	12,471
R-squared	0.737	0.727	0.775	0.766
County FE	✓	✓	✓	✓
Time FE	✓	✓	× State	× State
Controls	✓	✓	✓	✓

This table presents a regression analysis of county-level private credit volumes around the introduction of the LCR. The dependent variable is *ln(1+Private credit amount)*, the natural logarithm of one plus the amount of private credit outstanding in the county. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation.

Table 4: **Industry-level analysis: external financial dependence**

	(1)	(2)	(3)	(4)	(5)	(6)
			low EFD	high EFD	low EFD	high EFD
VARIABLES	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)
LCR footprint × post	0.763***		0.530	0.991***		
	(0.227)		(0.363)	(0.361)		
LCR gap footprint × post		3.009**			1.360	4.784***
		(1.269)			(2.257)	(1.825)
Observations	34,523	33,686	17,195	17,328	16,815	16,871
R-squared	0.743	0.743	0.743	0.742	0.740	0.745
County*SIC3 FE	✓	✓	✓	✓	✓	✓
Time FE	× SIC3	× SIC3	× SIC3	× SIC3	× SIC3	× SIC3
Controls	✓	✓	✓	✓	✓	✓

This table presents a regression analysis of industry-county-level private credit volumes around the introduction of the LCR. The dependent variable is *ln(1+Private credit amount)*, the natural logarithm of one plus the amount of private credit outstanding in the county. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation.

Table 5: **Liquidity versus capital regulation**

VARIABLES	(1) log(1+amt)	(2) log(1+amt)	(3) log(1+amt)	(4) log(1+amt)	(5) log(1+amt)	(6) log(1+amt)
LCR footprint × post (standardized)	0.546***		0.436***			
	(0.122)		(0.163)			
ST footprint × post (standardized)		0.398***	0.139			
		(0.111)	(0.152)			
LCR gap footprint × post (standardized)				0.324***		0.204*
				(0.101)		(0.108)
Tier-1 gap footprint × post (standardized)					0.402***	0.320***
					(0.094)	(0.103)
Observations	12,776	13,208	12,754	12,654	13,345	12,654
R-squared	0.737	0.734	0.738	0.727	0.733	0.729
County FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

This table presents a regression analysis of county-level private credit volumes around the introduction of the LCR and the FED stress test of 2012. The dependent variable is *ln(1+Private credit amount)*, the natural logarithm of one plus the amount of private credit outstanding in the county. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *ST footprint* is the deposit-weighted share of banks that were included in the FED stress test of 2012. *Tier-1 gap footprint* is the deposit-weighted tier 1 capital shortfall of banks, based on the stress test, in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation and the 2012 stress test.

Table 6: **Controlling for bank size, population density, and deposit HHI**

VARIABLES	(1) log(1+amt)	(2) log(1+amt)	(3) log(1+amt)	(4) log(1+amt)	(5) log(1+amt)	(6) log(1+amt)	(7) log(1+amt)	(8) log(1+amt)
LCR footprint × post	1.833***		1.785***		2.015***		1.711***	
	(0.546)		(0.461)		(0.450)		(0.547)	
LCR gap footprint × post		6.475***		7.121***		7.577***		6.399***
		(2.436)		(2.325)		(2.331)		(2.372)
Total assets footprint	0.000	0.001**					0.000	0.001*
	(0.001)	(0.001)					(0.001)	(0.001)
Pop density × post			0.105***	0.109**			0.103	0.045
			(0.038)	(0.045)			(0.066)	(0.081)
Deposit HHI × post					-0.170	-0.143	-0.064	-0.152
					(0.755)	(0.611)	(0.674)	(0.788)
Observations	12,363	12,126	12,776	12,654	12,776	12,654	12,363	12,126
R-squared	0.730	0.722	0.738	0.728	0.737	0.727	0.731	0.722
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

This table presents a regression analysis of county-level private credit volumes around the introduction of the LCR, controlling for bank size distribution by county. The dependent variable is *ln(1+Private credit amount)*, the natural logarithm of one plus the amount of private credit outstanding in the county. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation. *Total assets footprint* is the deposit-weighted average of total assets of the banks in the county. *Deposit HHI* measures local deposit market concentration as in Drechsler et al. (2017).

Table 7: **Alternative outcome variables**

VARIABLES	(1) IHS(amt)	(2) IHS(amt)	(3) log(amt)	(4) log(amt)	(5) Δ DHS amt	(6) Δ DHS amt
LCR footprint × post	2.165***		2.119***		0.244***	
	(0.480)		(0.547)		(0.071)	
LCR gap footprint × post		8.083***		8.094***		0.724**
		(2.494)		(2.692)		(0.328)
Observations	12,776	12,654	12,498	12,383	12,776	12,654
R-squared	0.724	0.714	0.763	0.754	0.060	0.061
County FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

This table presents a regression analysis of county-level private credit volumes around the introduction of the LCR. The dependent variable is shown above each column. *IHS(amt)* is the inverse hyperbolic sine of the amount of private credit outstanding in the county. *log(amt)* is the natural logarithm of the amount of private credit outstanding in the county. Δ *DHS amt* is the quarterly change in private credit volume. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation.

Table 8: **Leveraged loans and LBOs**

VARIABLES	(1) LL log(1+LL amt)	(2) LL log(1+LL amt)	(3) log(1+amt)	(4) log(1+amt)	(5) LBO log(1+amt)	(6) no LBO log(1+amt)	(7) LBO log(1+amt)	(8) no LBO log(1+amt)
LCR footprint × post	0.358		1.661***		0.922	1.550***		
	(0.359)		(0.475)		(0.560)	(0.411)		
LCR gap footprint × post		2.388		5.636**			3.420	6.431***
		(1.788)		(2.621)			(2.841)	(2.460)
log(1+LL amt)			0.026	0.047				
			(0.034)	(0.037)				
Observations	8,324	8,342	8,324	8,342	12,776	12,776	12,654	12,654
R-squared	0.813	0.814	0.750	0.735	0.648	0.752	0.646	0.744
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓

This table presents a regression analysis of county-level leveraged loan volumes as well as private credit volumes around the introduction of the LCR, also divided into loans for LBO financing and other loans. The dependent variable in columns (1) and (2) is *ln(1+Leveraged loans amount)*, the natural logarithm of one plus the amount of leveraged loans outstanding in the county. The dependent variable in columns (3) and (4) is *ln(1+Private credit amount)*, the natural logarithm of one plus the amount of private credit outstanding in the county. In columns (5) to (8), the dependent variable is *ln(1+Private credit amount)*, but only including LBO loans or non-LBO loans, as indicated above each column. In columns (3) and (4), we control for the contemporaneous amount of leveraged loans. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation.

Table 9: **Industry-level analysis: asset redeployability**

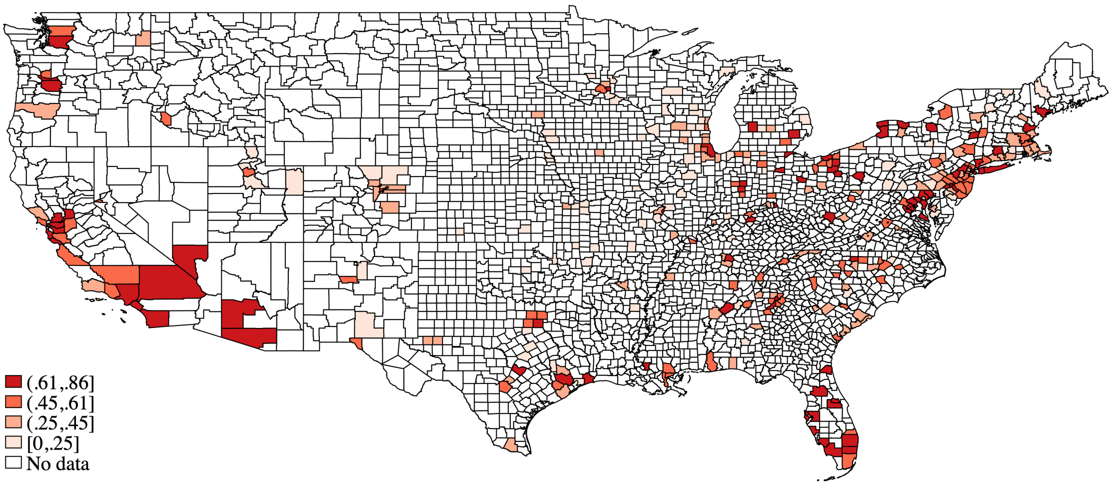
VARIABLES	(1) low AR log(1+amt)	(2) high AR log(1+amt)	(3) low AR log(1+amt)	(4) high AR log(1+amt)
LCR footprint × post	1.114***	0.436		
	(0.359)	(0.400)		
LCR gap footprint × post			4.147*	1.998
			(2.161)	(1.742)
Observations	16,068	11,550	15,634	11,410
R-squared	0.748	0.721	0.745	0.725
County*SIC3 FE	✓	✓	✓	✓
Time FE	× SIC3	× SIC3	× SIC3	× SIC3
Controls	✓	✓	✓	✓

This table presents a regression analysis of industry-county-level private credit volumes around the introduction of the LCR. The dependent variable is *ln(1+Private credit amount)*, the natural logarithm of one plus the amount of private credit outstanding in the county. *LCR footprint* is the deposit-weighted share of LCR banks in the county in 2012. *LCR gap footprint* is the deposit-weighted LCR shortfall of banks in the county in 2012. *Post* is a dummy taking the value of one from 2013 onward, after the introduction of the LCR regulation.

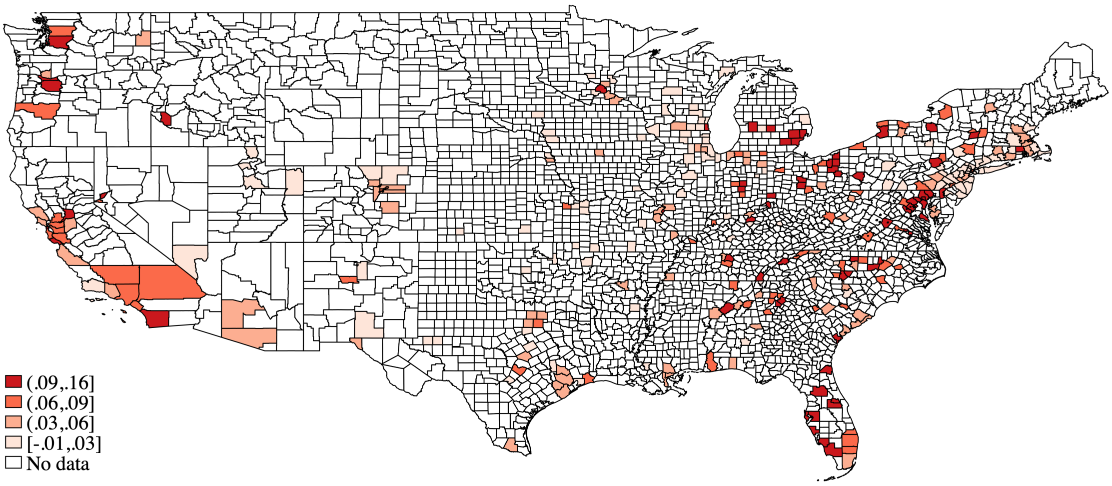
Internet appendix

Figure IA.1: **LCR footprint across counties**

(a) LCR footprint



(b) LCR gap footprint



This figure shows a map of U.S. counties with the respective values for *LCR footprint* and *LCR gap footprint* as of 2012.

Table IA.1: **Replication of Sundaresan and Xiao (2024)**

VARIABLES	(1) Loan growth	(2) Loan growth
LCR gap × post	-0.996***	-1.022***
	(0.313)	(0.314)
Observations	33,930	33,020
R-squared	0.143	0.285
Bank FE	✓	× MSA
Time FE	✓	× MSA
Controls	✓	✓

This table replicates Table 6 of Sundaresan and Xiao (2024) on small business lending of LCR banks. The dependent variable is the growth rate of small business loans.

Table IA.2: **External finance dependence and asset redeployability – without industry-time FE**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			low EFD	high EFD	low EFD	high EFD	low AR	high AR	low AR	high AR
VARIABLES	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)	log(1+amt)
LCR footprint × post	0.670***		0.067	1.167***			1.169***	0.439		
	(0.255)		(0.421)	(0.373)			(0.423)	(0.378)		
LCR gap footprint × post		3.061***			0.456	4.962***			4.026*	3.470**
		(1.120)			(1.966)	(1.749)			(2.130)	(1.566)
Observations	34,907	34,132	17,262	17,645	16,929	17,203	16,137	11,783	15,675	11,667
R-squared	0.714	0.714	0.715	0.718	0.713	0.720	0.722	0.694	0.719	0.699
County*SIC3 FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.3: **Leveraged loans + private credit**

VARIABLES	(1) LL+PC log(amt)	(2) LL+PC log(amt)	(3) LL+PC log(1+amt)	(4) LL+PC log(1+amt)
LCR footprint × post	0.999**		0.955	
	(0.480)		(0.585)	
LCR gap footprint × post		4.326**		3.779
		(2.185)		(2.530)
Observations	12,675	12,559	12,551	12,471
R-squared	0.891	0.890	0.903	0.903
County FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓